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ORIGINAL PAPER

Statactivism Up and Down the Stack: Dilemmas in the Estimation of AI's Environmental Footprint

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Abstract
With mounting concerns regarding the environmental footprint of AI systems, the number and diversity of actors engaged in evaluating the sustainability of machine learning (ML) and artificial intelligence (AI) more broadly is growing. Based on nine semi-structured interviews with key experts, this paper investigates the dilemmas active participants in this global project face and the strategies they employ to overcome them. Our analysis shows that experts question the extent to which quantification fosters a radical enough version of change. Some evaluators want to make AI systems more "efficient" by reducing the amount of resources needed to develop AI models and infrastructures. Others critique this approach for failing to limit overall carbon emissions. Instead they insist on making AI "frugal", an approach which expands the range of actions to mitigate AI's indirect environmental impacts and includes consideration of whether AI is needed at all in each specific context. This tension creates situations of emotional discomfort and divided loyalties at two key moments: access to funding and expertise. In some cases, it leads some contributors to build coalitions of workers inside and across companies in order to challenge management, or to leave their organizations altogether.

Keywords Artificial intelligence · Sustainability · Frugality · Quantification

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1 Introduction

Can quantification resolve AI's rising environmental footprint? The growing awareness of the environmental consequences of AI is largely due to experts who have produced quantified assessments of AI's impacts on the planetary climate system (e.g. Bender et al., 2021; Luccioni et al., 2020; Strubell et al., 2020). Researchers use a variety of methods such as predicting the sales of GPUs (IEA, 2024), estimating the impacts of AI across its life cycle (Ligozat et al., 2022), conducting surveys to gather the opinions of decision makers at large organisations (BCG, 2022) or building dynamic systems to adjust predictions of future energy consumption (Paccou & Wijnhoven, 2024). As a consequence of intensifying public discussions fostered by these numbers and other accounts of AI's impact on ecosystems (e.g. Ligozat et al., 2022), states and intergovernmental organizations are calling for regular, systematic and transparent AI environmental impact evaluations (e.g. Ebert et al., 2024; OECD, 2022), implying that more accurate understandings of the ways in which AI impacts the environment will lead to more effective measures to address those impacts. In this context, a global project of workers, activists and concerned researchers in industry, think tanks and the academy is emerging to investigate AI's environmental footprint. Professionals participating in this endeavor ask questions such as what a "good" assessment of AI's environmental consequences is, by defining the various categories of impacts (Kaack et al., 2022), the steps at which AI influences the environment (Ligozat et al., 2022) and the methods to measure impact at each of these steps (Luccioni et al., 2023). These methods diverge with on the one hand researchers developing bottom-up approaches that estimate the footprint of each individual component of AI's infrastructure and add them together, and on the other hand top-down methodologies that take sector-level indicators as a point of departure (Pasek et al., 2023). These numbers lead to discussions on potential solutions, such as limiting the size of models (Varoquaux et al., 2024), building and assigning tasks to task-specific models (Hoffmann & Majuntke, 2024), compressing models (Rafat et al., 2023) or reducing the cost of inference (Chien et al., 2023).

However, the extent to which quantification will address the fundamental issue of AI's role in expanding carbon emissions is debated. Numbers can be instrumentalized by a variety of actors to serve their interests. For example, some companies report their emissions using market-based methodologies that take into account the purchase of green energy. One estimation shows that this provides results that are six-times lower than those obtained by location-based methods that reflect the energy actually used in a given data center (O'Brien, 2024). Actors can also provide inaccurate or misleading information in order to downplay their effects on the environment. They can game the processes by which scientific communities are able to attain relative levels of accuracy in order to delay decision-making. At a more fundamental level, powerful actors can use quantification to reproduce the *status quo* by defining what and how it ought to be measured. More often than not, then, numbers serve a more reformist than radical attitude to change (Gruen, 2023).

Further understanding of what purposes are served by numbers on the environmental footprint of AI is paramount given the diversity of professional profiles involved in the nascent project of evaluating AI's impacts. Some of these professionals work in standardization body organizations, others in technology companies. Some have created or are employees of non-governmental organizations or associations focused on the environmental footprint of information technologies (IT), others are computer scientists in academic research laboratories. The participation of industry in these discussions raises questions regarding their ability to gain knowledge and influence decisions (Veale et al., 2023). Companies are a key source of revenue for the emerging economy of virtue in which AI ethicists participate (Phan et al., 2022). Interactions with industry are simultaneously sought after but also criticized, as commentators recall the active engagement of large industrial actors in creating controversies about the growing evidence of the impact of tobacco and pharmaceutical products on health (Oreskes & Conway, 2010), and more recently the strategies of the fossil fuel industry to peddle misleading science in order to delay climate action (Franta, 2022). There are fears that technology companies too will use quantification to exaggerate and greenwash their environmental credentials or obfuscate their ecological impacts (Hogan & Richer, 2024).

How do the participants in the global endeavor to estimate AI's environmental impacts understand and perceive these tensions, and how do the limits of quantification structure this emerging project? This paper uses in-depth interviews with nine key participants in the debates to investigate these tensions and the strategies active contributors to the conversation deploy to overcome them. In the next section we look at the evolving landscape of AI evaluation and, within it, the growing field of research on the environmental footprint of AI. The following section reviews some of the limits of quantification and introduces what French scholars have labeled "statactivism" as a concept to describe the experience of challenging authority with numbers. Questions and methods are presented in the next section, before turning to findings. The conclusion discusses the ways in which the limits of quantification structure the nascent field of AI environmental evaluation.

2 AI Evaluation and the Limits of Quantification

2.1 AI Environmental Impact Evaluation and the Governance of AI

The social and, increasingly, environmental consequences of artificial intelligence (AI) have garnered significant public attention in recent years as algorithms, automated reasoning and machine learning models are being integrated into more and more business, government and media processes. Concerns about big technology companies' collection and misuse of personal data in breach of privacy protections, the way in which they enable surveillance by advertisers and the state, the use of algorithmic social media to spread hate, misinformation and other potentially harmful content, exploitative labor practices, and monopolistic behavior led to the 'techlash' of the mid-2010s (Phan et al., 2022, p. 123). Concerns with the social and human rights risks of digital technology have only heightened with the widespread discussion and uptake of 'generative' or 'general purpose' AI machine learning models since the 2022 launch of Chat GPT, drawing on earlier debates about machine learning (e.g. Henderson et al., 2020). The 'race' (Koniakou, 2023) to build national and international governance frameworks to evaluate and regulate the risks of AI systems has become a pressing topic (Roberts et al., 2024; Veale et al., 2023). Several high profile inter-governmental and civil society networks have called for the creation of transnational scientific expert communities to act as international knowledge institutions (Miller, 2007) to develop a collective understanding of the risks of AI systems and how to reliably evaluate and govern those risks (Bengio, 2024; UN, 2024).

Evaluating AI's environmental footprint is becoming an important aspect of these international projects. While the main focus of attention is the governance of AI's risks to human health, safety and fundamental rights (European Parliament, 2024, Recital 1), the environmental sustainability of AI systems is also of increasing public concern. The final version of the EU AI Act includes environmental protection among its purposes (European Parliament, 2024, Recital 1, Article 1). The increased energy use associated with the computational power needed to support the massive expansion in development and deployment of AI in just a few years has been widely noted and reported (e.g. Ortar et al., 2022). One high profile issue is data centers: Sasha Luccioni of Hugging Face and colleagues have recently suggested that 'the amount of energy needed to power AI now outpaces what renewable energy sources can provide' in the United States (S. Luccioni et al., 2024). Additionally, the International Energy Agency forecasts a doubling in the energy consumption of AI between 2024 and 2026, resulting in AI electricity consumption equivalent to the whole of Japan (IEA, 2024). Reportedly their recent expansion of AI has meant that a number of big tech companies have failed to meet their climate targets (e.g. Halper & O'Donovan, 2024). The use of water to cool the hyper scale data centers needed for AI and other networked computation is also notable, creating conflict in regions where water is scarce (Dryer, 2023; Hogan, 2015; Lehuedé, 2024; Li et al., 2023).

Academics, practitioners and inter-governmental agencies have pointed out that every stage of the AI lifecycle can have negative environmental impacts, from the extraction of resources to build and operate new infrastructures (such as data centers and the undersea cables that connect them), the production of servers and microchips to work inside the data centers, the multiple edge devices needed for optimal personal and business deployment of AI in multiple applications, and the disposal and waste of infrastructure and devices (Kaack et al., 2022; Ligozat et al., 2022; OECD, 2022).[1] The diverse range of potential direct and indirect effects along this whole AI 'supply chain' (Cobbe et al., 2023) and its infrastructures makes AI's environmental impact complex to assess and measure (Kaack et al., 2022; Pasek et al., 2023). A key challenge is the ability to track and report environmental impacts through the chain so that the end users can make assessments about which systems to purchase and how to use them to minimize their environmental consequences. Another problematic issue is how to evaluate and report the application of AI for a diversity of more or less environmentally beneficial purposes ranging from the use of AI to fund ecocidal war drones, new fossil fuel exploration or synthetic targeted advertising for hyper consumption, to promises such as that AI will enable more energy efficient distribution of electricity and automobile traffic (Dauvergne, 2020; Hogan & Richer, 2024). As

[1] see also AlgorithmWatch (2023) and Robbins and van Wynsberghe (2022).

our discussion below shows, this has become a particular issue in the debate over efficiency vis a vis frugality as goals in AI environmental evaluation.

National and trans-national governance systems for AI, with the EU AI Act in the lead, are converging on a risk management approach in which developers and deployers of AI systems are mandated or encouraged to identify, analyse and manage their AI risks. To guide these approaches, standards for the evaluation and management of various AI risks are being developed by various industry, multi-stakeholder and inter-governmental organizations (Fraser et al., 2024; NIST, 2023; OECD, 2024). The European Commission published its official call for the development of a measurement framework for energy efficient and low emission AI in the EU in the second half of 2024 (European Commission, 2024).

In France, the standardization body, AFNOR (Association française de normalisation), organized one of the first systematic, government-sponsored attempts to gather experts to propose shared practices in order to develop a standard for evaluating systems and take actions to reduce AI's environmental footprint. This resulted in a benchmark for measuring and reducing the environmental impact of AI, 'A general framework for frugal AI' (AFNOR, 2024). Several groups of professionals in the digital technology industry as well as technology adjacent think tanks and civil society organizations have also made attempts to develop professional or common environmental impact of AI tracking and measurement frameworks (Gupta, 2021; S. Luccioni, 2025; Nafus et al., 2021).[2]

2.2 The Limits of Quantification

The environmental footprint of AI is notoriously difficult to measure. One factor making quantitative research challenging is the unavailability of data. For example, manufacturers share little information about the quantities of components they use to build the graphic processing units (GPUs) necessary for training and running foundation models. In addition, not all companies make the energy demands of their models transparent. As a result, researchers attempt to fill in the gaps by making estimations based on the little information they have. In some cases, they run their own experiments using infrastructures at public universities that are able to share data (Luccioni et al., 2023). Whilst these results are important to advance research in the field, they do not always reflect the reality of energy consumption inside private companies.

Beyond missing information, measuring the environmental footprint of AI represents a methodological challenge that parallels that of estimating information and communication technology's (ICT) footprint. Based on a review of quantification literature on the environmental footprint of ICT, Pasek et al. (2023) have shown that using bottom-up or top-down approaches, making decisions on what counts as ICT, relying on local measures or global averages and anticipating more or less strong efficiency improvements in future infrastructures, can alter the results by several orders of magnitude. Numbers on the environmental footprint of AI are similarly inconsistent. For example, usage can create important discrepancies. In their 2019 report,

[2] See, amongst many examples, CodeCarbon, the Green Software Foundation, the Green Web Foundation and the IEEE Sustainable ICT Initiative.

Microsoft and PwC anticipated a 4% global emission reduction due to AI improving efficiencies in the agriculture, energy and transport sectors (Microsoft & PwC, 2019). On the contrary, Schneider Electric attempts to include predictions reflecting the Jevons paradox to estimate energy demand increases of between 2 and 13 times their 2025 value (Paccou & Wijnhoven, 2024).

This diversity of numbers makes the measurement of AI's environmental footprint an opportunity for a variety of actors to defend their interests. Numbers often rely on an important work of classification that embodies values in determining what ought to be categorized and for what purpose (Bowker & Star, 2000). In particular, building numbers requires infrastructures to collect data for mathematical models (Desrosières, 2010). Quantification emerges from large-scale efforts to understand the world (Edwards, 2013) and is historically associated with State imperatives to develop tools of governance (Desrosières, 2010; Hacking et al., 1990; Porter, 2020). Quantification efforts are thus significant exercises of power that direct actions towards specific objectives to the detriment of others. As Berman and Hirschman (2018, p. 260) note, "there would be little reason to care about how numbers are produced absent evidence that such numbers had the potential to powerfully alter the trajectories of individuals, organizations, and fields."

There is a lot at stake in quantifying the environmental footprint of AI. In the most problematic cases, numbers can be manipulated (West & Bergstrom, 2020). Actors can willingly share outright false information about the phenomena they claim to study. They can also game the processes by which numbers are being produced. Whether a model is precise or accurate enough depends on the objectives of those who use it (MacKenzie, 1990). Precision and accuracy are therefore constantly debated and actors can seek to delay decision making until after reaching a more precise or accurate model. In other cases, large organizations can hire scientists to produce evidence that runs counter to existing studies and temporarily protects actors from political attacks (Franta, 2022). In both cases, actors spend time and resources to manufacture or exacerbate doubt in the hope of delaying action. In the case of AI's environmental footprint, quantification efforts can slow down significant investments in the mitigation of harms and the development of alternative models of development (Gregg & Strengers, 2024; Gritsenko et al., 2024).

At a more fundamental level, numbers tend to reproduce pre-existing forms of power. Defining metrics predetermines goals and forms of action to attain these goals (Desrosières, 2008). Whilst numbers can raise attention to specific issues, actors can develop strategies to produce the numbers they need to meet these objectives. The market-based versus location-based methods of carbon accounting mentioned above illustrates this point. Actors develop and use accounting methods that allow them to attain their objective of showing quantified emissions reductions, regardless of the material emissions that are released in the atmosphere. As numbers are internalized by powerful actors, quantification exercises may not lead to a radical enough vision of change (Boltanski, 2014). In addition, statistics often rely on numbers that are produced by institutions themselves, limiting the ability of numbers to empower individuals to act independently or against existing institutions.

Despite these critics of quantification, numbers can also be a source of emancipation. People seeking to challenge the *status quo* must often accept using numbers in order to convince others. Isabelle Bruno and her colleagues speak of "statactivism" to describe the "experiences aimed at reclaiming the emancipatory power of statistics" (Bruno et al., 2014, p. 8). Starting from the proliferation of numbers in a multitude of sectors such as arts, academia, politics and economy and their constraining effects on the agency of individuals, the authors document the quantification-based strategies available to free oneself from various forms of authority. One such strategy is to build categories that require attention and, in turn, determine a set of actions to be taken. Estimating the environmental footprint of AI requires defining the categories of impacts that must be assessed. In a recent effort to raise attention on the full range of effects of AI on the environment, Luccioni et al. (2025) have once again called upon the consideration of so-called rebound effects in global quantification efforts. This encourages a range of actions that go beyond building more efficient models to take into consideration systemic behaviours. Another strategy is to build new indicators. Whilst a lot of attention is devoted to estimating AI's energy demand and, to some extent, water usage, the research community stresses the importance of also considering the use of abiotic resources and the effects of building new data centers on biodiversity (Ligozat et al., 2022). More radical approaches also identify climate justice and the unfair distribution of the burdens of AI's usage of energy, water, and mineral resources on already disadvantaged communities (Kneese, 2023; Valdivia, 2024).

3 Questions and Methodology

Based on this review of literature, this paper investigates how AI evaluators working on standardizing the estimation of the environmental footprint of AI navigate tensions around quantification. People with a range of professional profiles – scientists, developers, advocates and civil servants – participate in the efforts to quantify the environmental footprint of AI. Standardization processes present situations where this diversity of participants come together to discuss and debate what counts as a "good" evaluation of AI's environmental footprint. In the course of these discussions, tensions around quantification and the form of change it fosters arise. Our aim was to interview experts who have participated in the development of methodologies to measure the environmental impact of AI to answer the following research questions:

RQ1 What tensions do active contributors to the debate perceive and how do they understand them?

RQ2 What strategies do they deploy to navigate these tensions?

RQ3 Which tensions remain unresolved?

3.1 Participants and Sampling

We interviewed nine active contributors to the debate on evaluating the environmental footprint of AI. Experts were considered contributors if they had participated in the publication of a report or academic paper assessing the environmental footprint of AI. Their contribution could seek to offer an estimation methodology, apply an existing method to a specific model or case study, or formulate a critique of current estimation efforts. In addition, we included experts who participated in and had an influence on the development of conversations around standards.

Our interviewees were selected through two streams. The first group of interviewees were chosen because they participated in the working group of the French standardization association (*Association française de normalisation*, AFNOR) on "frugal AI". AFNOR convened a working group of policy experts, developers and workers at technology start-ups and scientists who participated on a voluntary basis. Membership was free and anyone who justified working on AI and the environment was able to join. The group met over a period of 6 months between January and June 2024 to write a reference document for organizations seeking to estimate the environmental footprint of AI and take action to mitigate its impact. Then, we identified additional participants through snowballing. Contributors outside of France who had published on the environmental footprint of AI and who were mentioned by our initial participants were contacted to be interviewed.

In total, we selected nine interviewees who agreed to take part in our research project. Although this number is relatively modest, the in-depth nature of the interviews allowed us to conduct a solid first exploration of the tensions inherent in this quantification exercise. In addition, given the limited number of experts actively contributing to the debate in France and at an international level, we considered nine interviews to be appropriate. We were careful to include interviewees from at least two different locations - the United States and France, although French speakers are slightly more represented. The interviews were conducted between March and September 2024.

Rather than study how one particular profession approaches the use of numbers, our aim was to bring to light a range of views and experiences of the tensions around quantification to understand how they structure professional relationships and the emergence of a field of AI evaluation across multiple fields of expertise. There is a variety of professional profiles among our participants. Some work at technology companies on sustainability projects related to AI infrastructures. Others are part of public agencies and administrations that help the State to coordinate action to foster the emergence of standards and/or help organizations reduce the environmental footprint of their AI services. Still others work in academia and conduct state-of-the-art research to estimate AI's footprint. Finally, some work in NGOs in the field of sustainable ICT. Participants had often crossed professional boundaries, working in consulting before turning to public policy or in academia before industry. Our participants also have different levels of seniority. Some are at an early career stage whilst others have decades of experience. Our participants are summarized in Table 1 (immediately below). They are referred to by the number in the left hand column when quoted in Part 4 below.

3.2 Data Collection

The first author conducted the interviews, which each lasted just under one hour, having been scheduled to last one hour. The interviews took place on Google Meet

Table 1 Summary of interview participants' characteristics

Participants	Organization	Hybrid profile	Seniority	Country
1	Policy	Yes (business and policy)	Low	France
2	Industry	Yes (industry and academia)	Medium	United States
3	Industry	Yes (industry and academia)	High	United States
4	Policy	No	High	France
5	Policy	No	Low	France
6	NGO	No	Medium	France
7	NGO	No	High	France
8	Industry	Yes (industry and academia)	High	United States
9	Industry	No	High	France

and were recorded on the interviewer's phone in mp3 format. Six were conducted in French and three in English language. The files were then uploaded and transcribed on the platform TurboScribe, and those in French translated to English using ChatGPT for a preliminary translation and then double-checked and adjusted (for the sake of the second author and publication). Participants were given an information sheet about the research and asked to sign a consent form prior to the interview.

The interviews were semi-structured. After a brief presentation of the project, participants were asked some general background and context questions about their work. The substantive themes in the interview guide followed the three research questions asked in this paper. The first theme investigates their view of the state of knowledge on the environmental footprint of AI, what the community knows and what is missing. The second deals with quantification and explores experts' views on the consequences of quantification for climate change, the extent to which numbers could lead to action and the factors that could limit their impact. The third delves into experts' perceptions regarding their jobs and their professional contribution to the reduction of AI's environmental footprint.

The data was collected as part of the first author's doctoral thesis project with ethics approval following the Code of Ethics of the University of Milan and in line with the Charter of Fundamental Rights of the European Union and other international human rights conventions established to safeguard knowledge and its development. Authorization was granted by the doctoral management office and director of the PhD programme at the University of Milan.

3.3 Coding and Analysis

The authors used an inductive approach to code the interviews to remain open to the full range of themes emerging from the data. The first round of coding was conducted by the first author using QDA software and close reading and re-reading of the interview transcripts. The codes were adjusted and finalized in discussion between both authors after a second round of reading and re-reading of the interviews by both authors. The final codes are shown in the second column of Table 2. The third column describes what material within each interview was used as an indicator of each code. In discussion, the authors jointly aggregated the codes under three key themes (set out in the first column of Table 2 below) and proceeded with a final reading and

Table 2 Coding framework

Theme	Code	Description
Dilemmas of statactivism	Measurement to inform or delay action	Discussions on the extent to which quantification is necessary to take action for the climate
	Efficiency versus frugality	Discussions on whether estimation should lead to efficiency (the same usage with less resources) or frugality (involving a reflexion on usage)
Making statactivism work	Mobilizing / building audiences	Discussions about building networks to act within or from outside an organization or field of practice
	Leaving industry	Discussions about experts taking a radical approach in order to escape the tension
	Managing different facets of oneself	Discussions about the perception of having several personalities
Struggling with statactivism	Money and the perception of purity	Discussions about the need to earn a living and its effects on one's integrity
	Access to infrastructure and the perception of purity	Discussions about the benefits of having access to a expertise within a company and effects on one's integrity

coding of the data. The three key themes are used to organise the analysis in Part 4 of the paper. (A more detailed codebook is available upon request from the first author.)

4 Findings

4.1 Dilemmas of Statactivism

4.1.1 Measurement to Inform or Delay Action?

The actors we interviewed all contribute to an emerging project of using measurement to raise awareness of the breadth and diversity of issues that AI poses for achieving climate and other environmental sustainability goals. They participate in a form of "statactivism" in the sense that they seek to use measures of the environmental impact of AI to galvanize individual consumers and tech workers to take action in order to reduce AI's environmental footprint (Bruno et al., 2014). Numbers objectivize what the overall impact is and point to specific steps in AI's life cycle that are particularly energy- or resource-intensive. Ideally, this helps decision-makers take action in order to reduce AI's environmental footprint. Participant 8, a senior researcher at a large technology company, runs a project that seeks to quantify the emissions of software. They say,

> [Our goal is to include numbers in developers' workflows]. I don't care what the number is, because as long as the number is not zero, then it's more accurate. Right now, there's no number at all [...] so there is no friction.

Numbers lead individuals to think about some aspects of the work they do that they had not previously thought about. CO2 emissions need quantification to exist in the workflow of developers. Quantification thus makes CO2 emissions visible and incentivize developers to take them into account. In our participants' view, numbers create friction in the sense that they prevent developers from doing their work without minimal consideration for the environment.

However, contributors were ambivalent about whether quantification was always used to motivate the most environmentally sustainable actions. For example, participants pointed out that while numbers can be a powerful tool for those who seek radical action to defend the climate, it can equally be instrumentalized to advance private interests, and a range of stances in between. The first way in which participants indicated numbers could be instrumentalized against environmental sustainability is by delaying the need to take action for the climate. According to participant 6, who works at a French green technology association, companies often emphasize the need for precise measurement in order to delay taking action:

> When you go to the Green Tech Forum [...] most of the actors are involved in measurement. It bothers us because there's this idea that companies won't act until they've measured everything. There's a business around measurement—everyone is trying to sell the best tool to measure impact. The digital footprint just becomes another line on the accounting sheet. But we already know the levers for action, yet companies hide behind the need for measurement.

Participant 6 became conscious that industry actors were seeking to postpone action until after they had quantified the impact, despite the fact that, in participant 6's view, "we already know the levers for action" - amongst them, for example, building systems that take into account the carbon footprint of energy at a given time to reduce usage during heatwaves. The way our participant describes this tactic echoes the work of Oreskes & Conway (2010), who have documented the ways in which pharmaceutical and tobacco industries amplified doubt to delay action. The strategy is also utilized by fossil fuel industries today, who hire economists to produce numbers that overemphasize the cost of taking action, thereby delaying more radical but necessary transformations of policy and economies (Franta, 2022). This perceived effort to manipulate numbers has to be understood in the context of wider attempts to engage with scientific work with the primary aim of delaying action by eroding public and political support for climate policies (Lamb et al., 2020). Actually, this suspicion of industry seeking to use numbers to serve their own interests is so strong that participant 4, a senior civil servant who works in policy, commented on the AFNOR working group by saying,

> I was positively surprised by the fact that there was no bad faith throughout our discussions.

The second reason experts worry about the instrumentalization of quantification relates to the ways in which numbers narrow the scope of decision-making and of action. According to participant 3, who works at a technology company,

> KPIs, by their very nature, narrow the definition of what activity is going to be taken. We never actually have the conversation about how we change business, how we change the incentives that people are being rewarded for in companies, and then how we make money in ways that would be more sustainable than shipping more products.

This participant mobilizes two arguments to contextualize the power of numbers. The first is that quantifying excludes aspects of reality. Quantification relies heavily on the work of categorization (Desrosières, 2010) and prioritizes some considerations to the detriment of others. In the view of participant 3, the numbers used at their company and in industry more widely do not foster critical reflections on "how we change business". Indeed the KPI categories utilized by industry exclude this aspect of the quantification exercise. The second argument is that quantification consolidates the *status quo*. Once in place, the categories that are quantified structure social interactions and perpetuate power structures (Bowker & Star, 2000). Fundamentally, quantification tends to rely on categories determined by institutions (Boltanski, 2014). These numbers tend to lead to a reformist, rather than a radical, vision of change. According to participant 3, current quantification efforts reinforce the incentives to ship more products and therefore do more of the same, rather than fostering re-appraisal of what sustainability might entail.

The two reasons why experts worry about the instrumentalization of numbers by industry must be understood together. Creating numbers is a time- and resource-intensive exercise. The experts who participated in AFNOR's working group did so on a voluntary basis and for a period stretching over several months. As participant 5, who was part of the discussions, recalls,

> We had a plenary once a month and a meeting every week. We knew people couldn't attend every time.

Experts are concerned that if quantifying efforts lead to deceiving results that prevent more substantial and potentially more impactful actions for the climate to be taken, then a substantial amount of time and resources is wasted. Contributors therefore remain attentive to the ways in which quantification prevents discussions about the wider and deeper transformations needed to build a sustainable future. This echoes broader concerns about the degree to which smaller, incremental reforms to policies and practices can lead to meaningful change by raising awareness and preparing the ground for future reforms, or whether they are merely symbolic and act to legitimate harms caused by the current system (e.g. Gruen, 2023).

Some contributors note that conversations about the environmental footprint of AI do not have to be mediated by quantification. For example, participant 6 suggested disassembling digital devices during conferences to prompt attendees to perceive the materiality of digital technologies.

> We try to point out that while there are always new figures on AI's footprint, we already know AI pollutes […]. What really worries us is the hypergrowth of AI. It's accelerating as a sector —digital technology — that is already growing the fastest in terms of CO2 impact, when we should be reducing it instead.

This participant later referred to the need to 'talk about' and 'critique' the "cornucopia paradigm". The cornucopia paradigm refers to the belief in limitless technological and economic growth, on the assumption that economic prosperity will overcome any negative environmental impacts (Hornborg, 2003). For this participant, however, the hypergrowth of AI does create a pressing environmental challenge as "apps and websites are becoming more resource-heavy, contributing to device obsolescence, which leads to … more powerful infrastructures and devices to allow for even more resource-intensive apps, creating a cycle." In this landscape, focusing on quantification alone seems to be insufficient to address the climate crisis. Bringing attention to the materiality of digital devices is another way to make systems transparent (Cellard, 2022). In participant 6's view, physically disassembling digital devices may be a powerful strategy to complement quantification in creating 'friction' and making 'perceptible' raising awareness of AI's real material environmental impact.

The perception of the AI hype is shared by other contributors. As participant 5 notes,

> There's such a hype around generative AI […]. This sort of frenzy makes me quite fearful, it makes me more pessimistic because […] I think we'll eventually and very quickly be caught up by reality. And beyond being caught up by the reality [of the impact of AI on our limits in terms of energy and resources], we'll also be caught up by the limits of AI itself.

The "frenzy" around AI is here considered worrying because of the direct environmental cost of the hardware necessary to its development. As participant 6 noted in the previous quotation, AI is emerging in an industry that is already growing fast in its environmental impacts. But here our participant also argues that those who actively contribute to deploying and using AI, and therefore increasing its impact on the planet, may end up being disappointed by AI. This introduces a new question that quantification efforts will need to take into account: is AI worth it?

4.1.2 Efficiency and Frugality

One key challenge for scholars and experts quantifying the environmental footprint of AI is to take into account diverse categories of AI's effects, which can be broadly summarized as direct and indirect (Cobbe et al., 2023; Coghlan & Parker, 2023; Kaack et al., 2022; Ligozat et al., 2022). Direct effects are generated by the development of the AI system and can include the costs related to software development such as training and inference. Indirect effects include the uses to which AI systems are put, which can be both negative and positive. Both participants 1 and 5, who participated in the AFNOR standardization exercise, cared deeply about the usage of AI when estimating its environmental footprint. As participant 5 remarked:

> The question arose: can an AI used to find new oil fields be considered a frugal AI if it uses fewer data, fewer digital resources, etc.?

Given the risk of industry instrumentalization of numbers, contributors question the overall purpose of quantification. Some believe the aim should be to make AI greener by reducing its direct effects, particularly energy and water use. For example, solutions in the nascent field of Green AI include training models on smaller datasets or limiting the number of times a model is trained (Schwartz et al., 2020; Verdecchia et al., 2023). Others insist addressing AI's impact on the environment requires specific attention to its indirect effects, including the uses to which it is put. This perspective takes a more critical approach to quantification and recognizes that the final aim of quantification ought to be to help societies reach their climate targets, and other sustainable development goals. On this latter view, AI evaluators should therefore take into account the purpose for which AI is used. These considerations move the discussion from one around "efficiency" to one about "frugality", a term adopted by the French government in its AI strategy. The distinction between the two was a recurring source of debate for the contributors to the AFNOR working group (see Table 3 below).

In the "efficiency" logic, actors seek to minimize the cost of production of each unit of output. The output itself is therefore not included in the scope. In the "frugality" logic, however, actors question the extent to which the output is necessary and aligned with wider environmental objectives. Frugality considers both direct and indirect effects by including the purpose for which AI is built. There is a gradation in the continuum between efficiency and frugality. At the lowest level, actors can build more efficient systems, but these systems can be used to further exacerbate the climate crisis (e.g. using AI for oil extraction purposes). At an intermediate level,

Table 3 Differences between efficiency and frugality as formulated by the AFNOR working group on frugal AI, our translation (AFNOR, 2024, P. 21)

	Definition	Related concepts	Logic	Approach	Comments
Efficiency	Ability to optimize the use of resources to achieve a defined outcome.	Efficacy, optimization	In relative terms/ per unit The need takes priority - optimizing a solution deemed the best fit for the need.	Seeking a local optimum or a compromise on a highly constrained type of outcome.	Taking first-order effects into account to minimize them. Considering the stakeholders of AI.
Frugality	Ability to be satisfied with a level of outcome deemed sufficient by redefining uses and needs.	Sustainability, sufficiency	All encompassing The constraint on resources takes priority—seeking the solution that uses the fewest resources possible while providing a satisfactory response to the need.	Seeking a global optimum or a broad compromise on a level of outcome, which requires broadening or relaxing the need.	Considering both first-order and second-order effects to minimize negative environmental impacts. Taking into account all actors beyond just the immediate stakeholders.

they can build frugal AI systems that do not contribute to more energy demand or resource depletion. At the highest level, they can build frugal AI systems with a net positive impact on the planet: for any given category of impact (resources, energy, CO_2, water), the usage of the AI system saves resources and this impact outperforms the environmental cost of building the AI system.

4.2 Making Statactivism Work

The limits of quantification and the ways in which it can be instrumentalized are a source of preoccupation for AI evaluators. The participants in our sample developed three strategies to manage this tension.

4.2.1 Mobilizing / Building Audiences

The first strategy is to build a movement or community within an organization or field of practice in order to change current habits. In this situation, actors participate in the economy of virtue and attempt to raise ethical considerations in the technology sector from within (Phan et al., 2022). One key aspect of this strategy is to surround oneself with people who share similar values in order to build coalitions and expand networks. Participant 3, who works at a technology company, noted

> I've always advocated in my own research and writing that it's the colleagues that you have, regardless of the employer, that really matter to the kind of world and work culture that you want to role model. So I think it's really important to try and lead with the principles that you're bringing to your research and work with people that share those principles […].

Participants often expressed the need to surround themselves with like-minded individuals. This fosters feelings of belonging and cohesion. For example, participant 8, a social researcher at a large technology company, portrays their team as "a group of 5 in a sea of 70 - mostly machine learning folks - with an emphasis on actual human value". Participants place a strong emphasis on the ethical dimension of their work and, in their view, working alongside colleagues who share these values is key to advance their goals.

In order to build a community, interviewees 2, 3 and 8 organized regular meetings at their companies, inviting colleagues interested in climate issues to share their insights. This helped raise awareness about sustainability. The groups usually garnered the attention of senior management at the company, who at first provided the team with the means to develop services and ideas with environmental considerations in mind. The groups soon grew into small communities of interests sharing a common enterprise of addressing the consequences of the companies' technology on the planet.

Conflicts with management often emerge, however. In 2020, Timnit Gebru and Margaret Mitchell were famously forced to leave Google after writing a paper exploring ethical and environmental issues with Google's development of large language models (Bender et al., 2021; Tiku, 2020). There have been multiple other publicly reported examples of tech worker activism around big tech companies' ethics and environmental impacts with many subsequently departing or being fired (e.g. Kneese, 2023). Participant 2, who worked at a technology company, says.

> I have been talking to developers who are volunteers of big companies who are […] a little bit more militant and they're much more interested in organizing within their own workplaces to try to convince management to change their ways. And so that is a very different kind of strategy than basically trying to sell green software through its business use case.

Management often supports the idea that "selling green software" is a solution to the climate crisis. In contrast, some of our contributors advocate for a broader range of actions to mitigate the company's environmental footprint. This tension rests on the opposition between a logic of "efficiency" and that of "frugality" highlighted above. In participant 2's view, proponents of the "frugality" logic usually do not have enough leeway to change the ways of management. They must therefore actively organize themselves to gain power within their organizations. They mitigate the perception of the tension by strengthening their role in the company, challenging power structures and, ideally, fostering meaningful change. Building coalitions also rests on the hope that the company is eventually going to change, alleviating the tension in the future.

This strategy is not always successful, however. Often, it is temporary. As participant 2 notes,

> If you read The Innovator's Dilemma [an influential book about business and 'disruptive technologies'] and understand how difficult it is to change companies that […] can't yet see how they're going to survive from something new, then it becomes a pretty thankless task to be the internal entrepreneur. I think that can be very exhausting for people like me who are often charged with being the change agent or the influencer in the company. I think … I think that can get a little tiring.

Building networks can challenge power structures inside an organization or community of practice. However, it is extremely energy-consuming. When structures fail to change, it can lead to a feeling of exhaustion that pushes individuals toward more radical strategies.

4.2.2 Leaving Industry

A second strategy to resolve the tension is more radical. Some participants leave organizations that do not align with the frugality logic. Participant 3, who worked at a technology company, notes,

> You know ultimately I could not live with the tension of working for a company that was expanding carbon emissions at a time when it was claiming not to be, and I think more and more people will make that decision based on their own values and principles that I think need to be acted on now for climate, as

> opposed to just tolerating it for the interests of a secure paycheck. That's just not … it's not a compromise I'm prepared to make.

Leaving the company at which they worked freed themself from the tension. The contradiction is stated clearly: the company does not reduce its carbon emissions, it expands them. This formulation highlights a perceived form of hypocrisy given the company's public engagements for the climate, which makes the tension untenable in our participant's view. The reason why people would close their eyes on such an inconsistency is "the interests of a secure paycheck" that challenges "values and principles that need to be acted on now". Contributors must balance their values and interests for the climate with material conditions and decide whether they are ready to make a "compromise". There are important consequences associated with the tension and leaving the company is often a last resort.

Leaving the groups or organizations that do not embrace "frugality" can have liberating consequences. Participant 3 continues,

> What I've found liberating is having anyone as my potential audience. And also […] helping people with specific problems that are very particular to where they are in their career in that company, or what bigger transformations are happening in that company that I don't have to be a part of but that give me again this moment to influence things […].

For this participant, leaving their company increased their audience. At their company, they had to convince the same people in management. Outside, they can speak with a variety of interlocutors, who bring to their attention a diversity of situations on which they can have an impact. The participant finds satisfaction in continuing to "influence things" inside companies and regain agency by building new networks that put pressure on organizations from the outside.

4.2.3 Managing Different Facets of Oneself

A third and final strategy to manage the tension is to create internal boundaries between different parts of oneself. Participants 9 and 2, who both work at technology companies, shared extensively on the difficulties they face trying to combine their attachment to environmental issues with their day job. As we will see in Sect. 4.3.1, this can result in participants feeling metaphorically "schizophrenic" or divided in their loyalties. At an earlier stage, however, participants seek to bring together various facets of their personalities in the workplace. Participant 3 noted,

> Many people of my age who have been involved in the industry wanted to do something to bring together climate concerns with their day job.

In order to expand networks of like-minded people within and outside of their organizations, participants must interact with a variety of stakeholders. Participants develop strategies to engage with a diversity of audiences. Participant 6 works at a French association that does research and advocacy for green digital technologies. They said,

> When I talk to companies, I talk a bit about, I don't like that word at all, […] "innovation". The argument is that it's not necessary to use high technologies to innovate.

Our participant adopts the use of the word "innovation", which they don't like, in order to raise their audience's attention. Actually, participants often feel they need to learn to speak a new language when they engage with stakeholders. Participant 3 reflected,

> I think what has helped me is learning from other consulting firms who've come up with a language to get people to think very personally about climate, whether that's thinking about the holiday plans they have with their children, or thinking about where they grew up and whether they still live there, and what they know about the land that's changed there over the lifetime that they've known about it.

They build a language that mobilizes a variety of places, situations, and people that strengthen the perceptibility of the materiality of climate change. The association between these places and personal moments can trigger an emotional response that can lead to changes in behaviours. Boltansky and Thévenot speak of "economies of worth" (Boltanski & Thévenot, 2006) to describe the ways in which values structure moral judgments. By expanding the network of actors mobilized in the debate on the environmental footprint of AI, participants navigate between different "economies of worth" to convince participants. They stop using purely rational language in order to introduce personal lives, families and friends into the balance.

4.3 Struggling with Statactivism

When building numbers to challenge the authority of powerful technological players who deploy AI systems, participants are confronted with the limits of their efforts. They perceive that numbers can be instrumentalized by organizations and are in themselves insufficient to change the course of action. The extent to which numbers foster a radical enough version of change is a source of preoccupation for those who participate in this global quantification effort. There are two key moments when participants most clearly perceive these tensions. The first is when participants seek to access funding, the second when they seek to gain knowledge and expertise. In each case, participants' independence and ability to effectively challenge technology developers are at stake.

4.3.1 Money and the Perception of Purity

Access to funding is a recurring problem for participants in the debate. At an individual level, the salaries of those who work inside AI companies are dependent on the development of AI. The financial wellbeing of the companies that hire them therefore determines their own ability to expand their work. Interviewee 9 holds a senior position at a technology consulting firm. They note,

> There were really two stages [over the last years at company X]: one stage where we were earning lots of money and had generous ideas, and another stage where reality caught up with us and it became complicated. […] Also, one of our biggest clients is [an oil company]. So obviously, it makes things a bit schizophrenic.

The funding of green projects by companies is often perceived as a secondary objective to that of earning revenues according to those who work inside industry. Companies tend to move away from green objectives when times are difficult financially. In addition, companies often rely on money from industries that are considered to expand CO2 emissions and exacerbate the climate crisis. This can cause contradictory objectives within the organizations and a feeling of 'schizophrenia', or divided roles and loyalties, for those who seek to move their companies and lead them to reduce CO2 emissions whilst doing business.

At an organization level, participants often feel that green technology projects are conducted alongside projects with negative consequences for the planet. For example, participant 8, a senior researcher at a large technology company, reflecting on the development of so-called "AI for Green" projects (projects that seek to use AI for the environment), said:

> It just follows a long pattern of sprinkling little charity projects to make sure the tech industry is insulated from critique. […] like here's "for good" here, but it gives a free pass for a bunch of stuff that is really quite bad.

Some of the associations that work on the estimation of AI's environmental footprint are themselves dependent on external funding to run their operations. AI evaluators are very wary of where money comes from and the potential impact of a funder on a project. Participant 7 has had a long career in policy, working with intergovernmental organizations on AI policy and at think tanks. They note,

> I remember a moment when a big industrial actor wanted to finance our work and put money in our hands. We don't do that. You don't understand, doing this is stupid and can blow things up. It's crazy, it's counterproductive. You have to be at arm's length. It's imperative.

Keeping an appropriate distance from industry is crucial for the success of their policy project. This involves being attentive to where money comes from. The public's negative perception of industry money and its influence in politics is so strong that accepting private money could "blow things up." However, despite widespread awareness of this risk, projects in AI sustainability need funding, to cover basic administrative costs for coordinating expertise, communication and advocacy. As a result, experts in the field can spend a significant portion of their time fundraising. As participant 6, who works at a French green technology association, notes,

> We work with many actors, not necessarily large companies. I think of cooperatives, for example, [or associations and NGOs]. These are people who are generally more open to these issues, particularly the right to repair.

This participant makes a distinction between large companies and other organizations such as cooperatives and NGOs. In their view, large companies are not open to discussing sustainability issues such as the right to repair, but other organizations are willing to engage. This allows them to extend their network to companies or associations that share their goals. In their view, it is therefore possible to avoid problematic sources of money and preserve their purity. However, in other cases the very fact of engaging with funders confounds the possibility of remaining independent and creates tension. As participant 2, who worked at a technology company and on AI policy, notes,

> There's no clean money. If you're getting foundation money, money from donors, individual donors, this money is not coming from good places. I think part of what I find very exhausting about this job is that we're always having to fundraise. I don't really want to have drinks with donors or whatever.

In our participant's view, all money is associated with companies that expand CO2 emissions in one form or another. From this perspective, all financial relations between organizations seeking to reduce CO2 emissions and funders reveal a contradiction. Organizations that seek to address the climate crisis need to be complaisant towards the organizations that are able to fund them. This form of complaisance is sometimes accompanied by a feeling of powerlessness, which takes an emotional toll on those who need to fundraise, thus causing exhaustion.

4.3.2 Access to Infrastructure and the Perception of Purity

In addition to access to funding, gaining knowledge and expertise is another situation in which the purity of participants is at stake. The resource-intensive nature of the AI research field means that there are only a handful of companies that have access to the hardware necessary to run state-of-the-art projects. Thus, participants are eager to gain knowledge from inside these organizations. However, here too they must manage the right distance or view the way they are perceived within the community change. There is a sort of fascination regarding what happens inside private organizations. As participant 3, reflecting on their relationship with colleagues in academia after having worked in industry, notes,

> I've felt that people have stopped asking me for intellectual contributions, and are more interested in the sort of … It's almost like the gossip of what it's like to be in a company. (…) I'm seen more as an industry insider rather than a fellow intellectual.

Working at a technology company changes how others perceive their work. Some companies actively engage in discussions about the environmental footprint of technology, including within academic circles. Notably, some significant papers have been published by researchers affiliated with large organizations (Wu et al., 2022). However, participants in these debates approach such contributions with caution. Despite this skepticism, stakeholders remain eager to gain insights into the inner workings of these companies. From our interviewee's perspective, there is a tradeoff: working outside the industry allows one to be regarded as a fellow intellectual, while working within it leads to being seen primarily as a valuable source of information.

5 Conclusion

Our analysis has shown that contributors to the debate on the evaluation of the environmental impact of AI use and adapt various strategies of statactivism (Bruno et al., 2014) in order to challenge Big Tech: they create collective categories to defend the interests of the planet by estimating the quantities of water, CO2 or energy that are necessary to build, train or deploy AI models. They also encourage the creation of new indicators that can steer industry's actions towards what they deem are more necessary actions for the climate. In doing so, contributors continuously circle around dilemmas inherent to the use of statistics to inform policy and practice: do numbers foster radical enough change? Does quantification help align consumer and business activity within environmental thresholds or does it reinforce existing power structures contributing to climate and other eco-impacts and injustices? Participants working in industry are constantly reminded of the relationships they share with organisations that expand CO2 emissions. They must fund their activities and actively engage with organisations and individuals that may otherwise give little attention to the climate crisis. They must also gain access to expertise inside companies.

Our analysis relies on a relatively modest number of interviews. Nevertheless, the tensions we highlight emerge across different fields of expertise, with participants working in industry, at NGOs, in ministries and in standardization organizations. In addition, although the tensions may manifest themselves differently across locations, the key themes and challenges are consistent. For example, US participants expressed strong opinions against all businesses due to their perceived role in expanding CO2 emissions, while French participants express similar concerns about more specific sectors such as oil and gas. Participants from both countries highlight concerns about whether usage is included when considering the ecological impact of AI.

Participants are very much aware of the tensions of quantification. On the one hand, measuring AI's footprint seems essential for raising awareness and informing decision-making. On the other hand, it limits the scope of action and self-interested actors may use it to delay necessary yet already identified actions. Given this tension, one group views AI's increasing impact on the environment as an efficiency problem, believing that it can be solved by making AI systems more efficient. The other group argues that tackling climate change will require significant reductions in resource consumption, moving beyond efficiency and into frugality, a notion that directs action towards identifying alternative business models for a more sustainable future. In particular, frugal AI involves a critical examination of the conditions in which AI is necessary and does not always need quantification.

In this context, the most engaged participants aim to persuade management to "change their ways" by building coalitions of workers within and across companies to challenge decision-making. Numbers play a crucial role in these social movements. Quantification is central to raising awareness of AI's and technology's impact on the planet and serves as a justification for further action. However, our participants believe that significant change will only occur when efforts extend beyond the scope of quantification. Actions taken to reduce CO2 emissions and energy consumption within the realm of AI primarily focus on improving efficiency. Yet, much more needs to be done beyond AI—and beyond quantification—to achieve meaningful reductions in carbon emissions and address unjust environmental impacts of AI supply chains. This presents a fundamental challenge for experts in quantification, who must develop solutions outside their immediate field of expertise.

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Data Availability The data that support the findings of this study include personal information about the participants. To preserve the anonymity of our interviewees, the data are available from the first author upon reasonable request.

Declarations

Competing interest The authors have no competing interests to declare.

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